An MINLP model to support the movement and storage decisions of the Indian food grain supply chain

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Abstract:

This paper addresses the novel three stage food grain distribution problem of Public Distribution System (PDS) in India which comprises of farmers, procurement centers, base silos and field silos. The Indian food grain supply chain consists of various activities such as procurement, storage, transportation and distribution of food grain. In order to curb transportation and storage losses of food grain, the Food Corporation of India (FCI) is moving towards the modernized bulk food grain supply chain system. This paper develops a Mixed Integer Non-Linear Programming (MINLP) model for planning the movement and storage of food grain from surplus states to deficit states considering the seasonal procurement, silo capacity, demand satisfaction and vehicle capacity constraints. The objective function of the model seeks to minimize the bulk food grain transportation, inventory holding, and operational cost. Therein, shipment cost contains the fixed and variable cost, inventory holding and operational cost considered at the procurement centers and base silos. The developed mathematical model is computationally complex in nature due to nonlinearity, the presence of numerous binary and integer variables along with a huge number of constraints, thus, it is very difficult to solve it using exact methods. Therefore, recently developed, Hybrid Particle-Chemical Reaction Optimization (HP-CRO) algorithm has been employed to solve the MINLP model. Different problem instances with growing complexities are solved using HP-CRO and the results are compared with basic Chemical Reaction Optimization (CRO) and Particle Swarm Optimization (PSO) algorithms. The results of computational experiments illustrate that the HP-CRO algorithm is competent enough to obtain the better quality solutions within reasonable computational time.

Keywords: Food grain distribution problem, Transportation, Inventory, Mixed Integer Non-Linear Programming, Chemical reaction optimization,

1. Introduction

Recently, the Government of India (GOI) has implemented the National Food Security Act (NFSA), 2013 across the country including all states and Union Territories for providing the food and nutritional security. This act is the key initiative for ensuring the food security which can be defined as economic access to the adequate quality food. Under this act, the targeted beneficiaries can get the highly subsidized food grains, i.e. wheat, rice, and cereals through PDS. The NFSA includes the 75% rural population and 50% urban population which makes the overall coverage of two third (67%) population of India (http://dfpd.nic.in/nfsa-act.htm). In order to provide the food grains to the large volume of the population, India has to increase its production, procurement and reduce the losses during transportation and storage. The major food grain supply chain related activities including procurement, storage, movement and distribution are taken care by the Central nodal agency called FCI. The procurement is carried out in the procurement centers of surplus states by FCI and State Government Agencies (SGAs) at the rate of Minimum Support Price (MSP). Normally, the different food grains procured in different seasons such as in Rabi season (April to June) wheat is procured and in Kharif season (October to February) Rice procures. FCI takes over the procured stock of food grain from SGAs and stores in its own warehouses of producing states. Next, GOI allocates the food grains to various deficit states and Union Territories based on their demand and offtake of the previous period. In consuming states, food grain stock is moved from regional warehouses to block level and block level to Fair Price Shops (FPS). Generally, FCI prefers the road mode for intra-state transportation and rail mode for inter-state transportation. All these major food grain supply chain activities are depicted in Fig. 1.

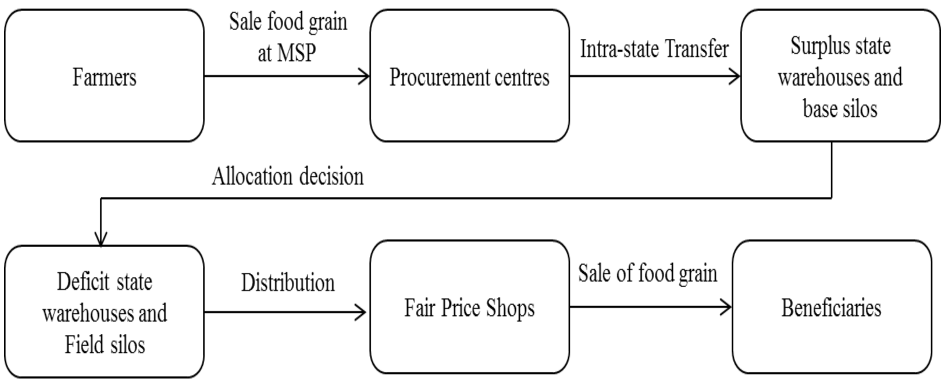

Fig. 1. Major activities of FCI

The Indian PDS is world's largest distribution system and its management is a complex issue due to the involvement of many entities such as FCI, SGAs, Railways, transporters and private contractors. In the conventional method, food grain is stored in godowns and transported using the gunny bags which has several flaws. The first and paramount important shortcoming is the huge amount of transportation and storage cost. FCI transports the 40 to 50 million tons of food grains across the country in a year through rail, road and waterways which incurred the average expenditure of 47.2737 billion (Comptroller and General of India (CAG), 2013). The FCIs total storage capacity including hired one was 336.04 Lakh Metric Tonne (LMT) as against the central pool stock of 667.89 LMT at the end of the March 2012 thus leaving a huge gap of 331.85 LMT. Next, the inadequate storage management practices and unclear norms of operational and buffer stock maintenance of deficit state leads to increase of food grains holding cost. In addition to the above inadequacies, FCI is also facing the problem of food grain losses which mainly occurred from post-harvest to distribution stage of food grain supply chain, i.e. during storage and transit. The shortages of labours and their huge salaries (handling cost), shortages of different capacitated vehicles (rakes and trucks), demurrage payment, carry over charges, and loading and unloading time are some of the other major challenges.

To tackle the aforementioned challenges, GOI is moving towards the modernized food grain supply chain system of bulk grain handling, transportation and storage. In this modernized system, food grain (wheat) is transported in bulk form using the truck as well as specially designed wagons and stored in steel silos. The silos located in the surplus and deficit states are known as Base silo and Field silo, respectively. Proper planning and coordination among all the entities of the food grain supply chain network can reduce the transportation as well as inventory cost and helps to take the various timely decisions such as "how much quantity to be transferred from which origin node to which base silo and from which base silo to which field silo." Similarly, the determination of each type of capacitated vehicles used for shipment between different entities is also the crucial aspect of food grain supply chain problem because the sufficient availability of capacitated vehicles helps for quick transfer of food grain from producing states to consuming states. Furthermore, FCI has to maintain the optimal level of operational and buffer stock in each silo for food security purpose. This paper considers the initial three stages of food grain supply chain network, including the origin nodes (farmers), procurement centers, base silos and field silos. An MINLP model is formulated after the critical analysis of Indian food grain supply chain network and various reports on PDS. The solution of the model will be helpful to FCI for taking the timely intra-state as well as inter-state movement and storage-related decisions. This paper extends the work carried out by the Mogale et al. (2016) and differ in following aspects. Here, 1. Three stage food grain distribution network is considered where food grain can be shipped from an origin node to procurement centers or base silos, 2. Inventory and operational costs considered at procurement centers and base silos, 3. Included the new vehicle capacity related constraints, 4. Different problem instances of the formulated MINLP model are solved using the recently developed HP-CRO algorithm and attained results compared with the CRO and PSO results. 5. Furthermore, the convergence behavior and movement along with storage activities of few selected instances are analyzed in detailed.

The remaining article is organized as follows. Section 2 presents the critical review of related work. In Section 3, the detailed delineation of considered problem is provided. The mathematical model with notations, objective function and constraints are illustrated in Section 4. Section 5 discusses the solution approach employed for solving the mathematical model. Section 6 depicts the results and analysis of computational experiments. Conclusion and future scope of the study is given in Section 7.

2. Related work

The supply chain distribution problem in the context of manufacturing industries has been widely addressed by several researchers in the past. The existing relevant works focusing on food supply chain related problems including inventory-transportation, post-harvest loss minimization, food distribution system and their solution methodologies, review papers along with advanced control techniques in agricultural systems have been described in this section. Recently, the real-world optimization problem of wheat transportation and storage in Iran has been effectively addressed by Asgari et al. (2013) by formulating the problem as a linear integer programming (LIP) model. The LINGO optimization software was used to solve LIP model and obtained results compared with the Genetic Algorithm (GA) which takes reasonable computational time for solving large size problems. Authors have not taken into account the different capacity and availability of transportation vehicles. An MINLP model has been formulated considering rail road flexibility by Maiyar et al. (2015) to optimize food grain transportation problem of Indian PDS. The food grain storage cost and capacity constraints of transportation vehicles are absent in their model. In the same domain of Indian food grain supply chain, Mogale et al. (2016) developed the two stage MINLP model for efficient transportation and storage of food grain from surplus states to deficit states. They have tested the model on single small size problem instance and results were not compared with other evolutionary algorithms. A deterministic mathematical model was proposed by Reis and Leal (2015) for optimization of tactical decisions of soybean supply chain in Brazil. Lamsal, Jones and Thomas (2016) dealt with the problem of minimization of a number of trucks entailed for transportation of harvested crops from field to storage point under the scenario of several independent farmers and absence of on-farm storage. In two-phase solution approach, initially, they fixed harvest starting time, then find out the number of trucks and their allocation to load. Ma et al. (2011) worked on the shipment consolidation problem of distribution network which involves manufacturers, cross docks and customers. They tried to minimize the trade-offs among movement cost, storage cost and scheduling requirements.

In order to reduce the post-harvest loss (PHL), Nourbakhsh et al. (2016) presented a mathematical model with the objective function of minimizing infrastructure investment and economic cost from PHL of food grain supply chain network. The main aim of this study was to determine the optimum new pre-processing facilities locations and transportation network capacity growth. Liu et al. (2016) critically analyzed the macro-level trends of food waste in Japan from 1960-2012 for additional prevention and mitigation of food waste. In this analysis, they have determined the mismatch between calorie/protein supply and consumption, elucidated the present status of waste in Japanese food supply chain and recommended the policies. Furthermore, An and Ouyang (2016) developed the bi-level robust optimization model with objective functions of profit maximization and PHL minimization of a food company. They have modelled a three stage food supply chain network considering the farmers, storage facilities, and export markets. The decomposed single-level problem has been solved using the Lagrangian relaxation algorithm and applied to Illinois and Brazil case studies. To compare the conventional rail service accompanied by country elevators with shuttle service accompanied by terminal elevators of U.S., Hyland, Mahmassani and Mjahed (2016) developed three models of domestic grain transportation including trucking, elevator storage, and rail shipment. These three models determine the travel time, variable cost and rail network capacity, respectively.

Rancourt et al. (2015) solved the distribution center location problem in the perspective of the food aid delivery system in Kenya with the help of Geographic Information System (GIS) data, need assessment and population data. They designed last-mile food supply chain network using real-time data of Garissa region in Kenya. A novel discrete/continuous time mixed integer programming (MIP) model is proposed by Kopanos et al. (2012) considering the families of products for simultaneous production and logistics operations planning in semi-continuous food industries. Furthermore, two industrial case studies of Greek dairy industry have been effectively solved using proposed approach. Moreover, Etemadnia et al. (2015) developed the mixed integer linear programming (MILP) model for minimization of total network cost containing transportation and facility location cost with two potential shipment modes for the design of the optimal hub logistic network for efficient transfer of food from production region to consumption region. To minimize the handling cost of Canadian wheat supply chain under the new declaration system, Ge, Gray and Nolan (2015) developed the analytic and agent-based simulation models assuming individual behavior and farmers as well as handlers as rational and learning individual, respectively.

In the domain of fresh food supply chain, Soto-Silva et al. (2016) critically reviewed the existing literature focusing on the operational research models employed to the fresh fruit supply chain problems. They identified some of the major challenges of fresh fruit supply chain problem such as long supply lead time, the disparity in supply and demand. An extensive review of state of the art in the domain of production and distribution of crops has been carried out by Ahumada and Villalobos (2009). They have divided the existing literature into three contexts based on storability of products (perishable and non-perishable), scope (strategic, tactical and operational) and modeling uncertainty (deterministic and stochastic).

In recent years, many solution methodologies like metaheuristics, optimization solver and two stage approach, etc. have been employed in the literature to solve the different food supply chain related problems depending on the problem complexities. A strategic vehicle routing and assignment problem of the dairy industry in Canada has been effectively solved by Masson, Lahrichi and Rousseau (2016) using the two-stage approach which depends on adaptive large neighboured search (ALNS). The primary and secondary stage solves the transportation and processing plant allocation problem, respectively. Jawahar and Balaji (2009) proposed a GA based heuristic method to solve the mathematical model of fixed charge distribution problem in the two-stage supply chain. The performance of proposed GA was compared with approximate and lower bound solutions. Furthermore, a two-stage fixed charge transportation problem (FCTP) was addressed under two situations by Antony Arokia Durai Raj and Rajendran (2012). They have considered the fixed cost, variable cost and unlimited Distribution Centres (DC) capacity in the first situation and variable cost from plant to DC, from DC to customers and DC opening cost in the second situation. Therein, they used the paired comparison *t*-test to evaluate the performance of proposed GA with best existing algorithms. Mousavi et al. (2015) examined the two-echelon distributor-retailer supply chain network design problem considering various seasonal products and shortage as an integration of the backorders and lost sales. They have implemented the modified fruit fly optimization algorithm (MFOA) to solve the developed mixed binary integer programming model and results were compared with other two algorithms namely PSO and Simulated Annealing (SA). A CRO inspired from the chemical reaction was established by Lam and Li in 2010 and effectively implemented to solve the real life Non-deterministic polynomial (NP) hard problems such as Quadratic assignment problem (QAP), resource-constrained project scheduling problem (RCPSP) and channel assignment problem (CAP). Truong, Li and Xu (2013) efficiently solved the 0–1 knapsack problem (KP01) using the chemical reaction with greedy strategy (CROG) algorithm which based on CRO structure and a greedy strategy. Also, Li and Pan (2013) studied the flexible job shop scheduling problem considering flexible preventive maintenance activities and suggested the hybrid chemical reaction optimization (HCRO) as a solution approach. In order to solve continuous optimization problems, Lam, Li and Xu (2012) proposed the new variant of CRO called real coded chemical reaction optimization (RCCRO) considering the Gaussian distribution.

Few authors have utilized the various advanced control techniques in agricultural systems and food engineering field for solving the supply chain related problems. Saint Germain et al. (2007) worked on supply network coordination problem and discussed a multi-agent coordination approach with factory control to manage the outbound and inbound logistics in multiple site/multiple organization topologies. To solve the Emergency Supply Chain (ESC) problem of supply of resources to the crisis-affected areas, Othman et al. (2017) proposed the Decision Support System (DSS) based on multi-agent architecture and optimization tools. A dynamic pickup and delivery problem with dial-a-ride service system has been addressed by Núñez et al. (2014) through a multi-objective model based predictive control method. The user and operator cost were considered the two conflicting dynamic objective functions. In order to improve the temperature control and curtail the electricity cost in cold storage facilities for agricultural produce (potatoes and onions), Lukasse et al. (2009) employed the receding horizon optimal control (RHOC) technology. A brief summary of aforementioned relevant works with main features is given in Table 1.

Table 1 A summary of relevant works in the literature

Authors and Year	Single/Multi period	Single/Multi product	Model	Objective/features	Solving method
Asgari et al. (2013)	Multi	Single	LIP	Minimization of the transportation and storage cost	LINGO and GA
Maiyar et al. (2015)	Single	Single	MINLP	Minimization of the transportation cost	Self-learning particle swarm optimization (SLPSO) and Particle Swarm Optimization with Composite Particles (PSOCP)
Mogale et al. (2016)	Multi	Single	MINLP	Minimization of the transportation , storage and operational cost	CRO
Reis and Leal (2015)	Single	Multi	LP	Maximization of profit	CPLEX 12.5
Lamsal et al. (2016)	Multi	Multi	MIP	Minimization of a number of trucks for crop transportation	GUROBI OPTIMIZER 5.6.
Ma et al. (2011)	Multi	Single	Integer programming	Minimization of transportation and holding cost	Two-stage heuristic algorithm
Nourbakhsh et al. (2016)	Single	Single	MIP	Minimization of infrastructure investment and economic cost from PHL	Case study
Liu et al. (2016)	-	-	-	Critically analyzed the macro-level trends of food waste in Japan from 1960-2012 for additional prevention and mitigation of food waste	-
An and Ouyang (2016)	Single	Single	MINLP	Maximization of profit and post-harvest loss minimization	Lagrangian relaxation algorithm
Hyland et al. (2016)	Multi	Single	Analytical model	Determine the travel time, variable cost and rail network capacity	Numerical method
Rancourt et al. (2016)	Single	Single	MILP	Minimization of the total welfare cost	CPLEX 12.5
Kopanos et al. (2012)	Multi	Multi	MIP	Minimization of inventory, operating, batch recipes preparation, unit utilization, families changeover and transportation costs	CPLEX 11
Etemadnia et al. (2015)	Single	Multi	MILP	Minimization of total network cost including facility location and transportation cost	Heuristic
Ge et al. (2015)	Multi	Single	Analytic linear	Minimization of handling cost	Simulation analysis

Table 1 Continue

Soto-Silva et al. (2016)	-	-	-	Critically reviewed the existing literature focusing on the operational research models employed to the fresh fruit supply chain problems.	-
Ahumada and Villalobos (2009)	-	-	-	Extensive review of the state of the art in the domain of production and distribution of crops	-
Masson et al. (2015)	Multi	Single	MINLP	Minimization of distance	Adaptive large neighboured search
Jawahar and Balaji (2009)	Single	Single	MINLP	Minimisation of the total cost of distribution	GA
Antony Arokia Durai Raj and Rajendran (2012)	-	-	MINLP	Minimization of fixed, variable and opening cost	Two stage Genetic algorithm
Mousavi et al. (2015)	Multi	Multi	Mixed binary integer programming	Minimization of total supply chain cost including transportation, holding, shortage, and purchase costs.	MFOA
Germain et al. (2007)	-	-	-	Discussed a multi-agent coordination approach with factory control to manage the outbound and inbound logistics in multiple site/multiple organization topologies	-
Othman et al. (2017)	-	-	MILP	Minimization of the delivery costs of resources, the earliness penalty and the tardiness penalty	Branch and Bound Algorithm
Núñez et al. (2014)	-	-	Non-linear programming	Minimization of user and operator cost	GA
Lam and Li (2010)	-	-	-	A CRO inspired from the chemical reaction was developed	-
Truong et al. (2013)	-	-	-	Maximization of profit (0–1 knapsack problem)	CROG algorithm
Li and Pan (2013)	-	-	-	Minimization of the maximum fuzzy completion time	HCRO
Lam et al. (2012)	-	-	-	Propose a real-coded version of CRO considering the Gaussian distribution for solving the continues optimization problems	RCCRO

In the past, very few researchers have focused on food grain distribution problems. Nowadays, due to the advances in technology, food grain is transported, handled and stored in bulk form rather than conventional methods. There are a limited number of studies available in bulk food grain supply chain domain. Therefore, the bulk food grain transportation, handling, and storage problem is investigated here considering deterministic procurement, demand, capacitated silos, and different capacitated vehicles in the finite planning horizon.

3. Problem background

In this study, the food grain supply chain problem of PDS in India is considered with the objective to minimize the transportation, handling and storage cost. There are several entities like farmers, FCI, various SGAs of surplus states, Railways, private contractors, etc. presents in the Indian food grain supply chain which makes it complex and unique compared with other food supply chain problems. The improper coordination and planning among these entities lead to the increase of food losses and other costs. Farmers take their food grains to nearby procurement centers using different capacitated vehicles such as tractors, small trucks, etc. for selling to FCI and SGAs at the rate of MSP. This procurement would take place in two seasons, i.e. Wheat is procured in Rabi marketing season (April-June) and Rice in Kharif marketing season (October-February). In this paper, we have considered several villages into one cluster and named it as origin node, so quantity available at each origin node is the sum of all the villages quantity considered in that cluster. The food grain from procurement centers is transported to base silos which are located in surplus states. The silos located in India are normally used for storing wheat only, therefore we considered a wheat supply chain. Recently, GOI has announced that the base silos will also work as procurement centers during the Rabi marketing season. Thus, farmers can sell their produce to either procurement centers or base silos depending on their requirements. Next, on the basis of deficit states demand and their offtakes in the previous period, GOI distributes the food grain to various deficit states. Food grain from base silos is transported to field silos which are located in deficit states using the specially designed wagons of rail rakes. Intra-state movement of food grain is mostly carried out by road. The overall scenario of these three stages is explained in pictorial form in Fig. 2.

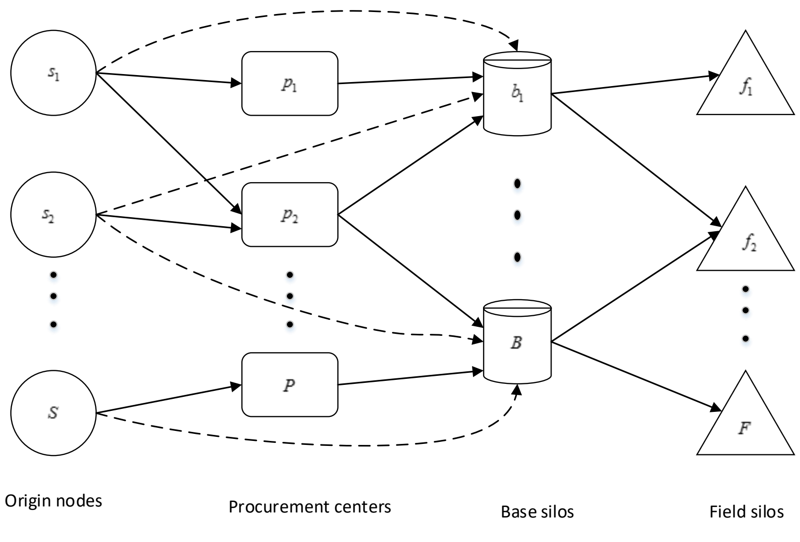

Fig. 2. The depiction of food grain supply chain network

The food grain movement in all three stages is mainly affected by several constraints about each stage. Major constraints include the food grain quantity available at each origin node, the capacity of procurement centers and base silos, the demand of field silos, timely availability of different capacitated vehicles (trucks and rakes) at each stage, fixed as well as the variable cost of vehicles and operational and buffer stock maintenance. This problem aims to find out the effective and efficient storage and movement plan of food grain supply chain which minimizes the transportation, handling and inventory cost. The next section presents the MINLP formulation of the considered problem.

4. Mathematical model formulation

Various assumptions considered and notations used while developing the model are described below:

4.1 Assumptions:

1) The every origin node represents the cluster of villages.
2) The procurement quantity, the capacity of procurement centers, base silos and demand are well known and deterministic.
3) The truck and rake types along with their availability are limited at respective stages.
4) The amount of food grain procured is adequate to fulfill the demand of each field silo.
5) The field silos demand must be satisfied during the particular time period.

4.2 Notations

The following notations have been used to formulate the model.

4.2.1 Sets/indices

T	Set of time periods indexed by $t \in T$
S	Set of origin nodes indexed by $s \in S$
P	Set of procurement centers indexed by $p \in P$
B	Set of base silos indexed by $b \in B$
F	Set of field silos indexed by $f \in F$
I	Set of trucks between origin nodes, base silos and procurement centers indexed by $i \in I$
J	Set of trucks between procurement centers and base silos indexed by $j \in J$
K	Set of rakes between base silos and field silos indexed by $k \in K$

4.2.2 Parameters

fc_{sp}^{i}	fixed cost for trucks of type *i* used on arc *(s, p)*
fc_{sb}^{i}	fixed cost for trucks of type *i* used on arc *(s, b)*.
fc_{bf}^{j}	fixed cost for trucks of type *j* used on arc *(p, b)*

fc_{bf}^{k}	fixed cost for rakes of type k used on arc (b, f)
vc_{δ}	variable cost of food grain transportation by road (unit cost/km i.e. per Metric Tonne (MT) per km)
vc_{ρ}	variable cost of food grain transportation by rail (unit cost/km i.e. per MT per km)
$cinv_{p}$	Inventory holding cost per MT quantity of food grain per time at procurement center p
$cinv_{b}$	Inventory holding cost per MT quantity of food grain per time at base silo b
$coper_{p}$	Operational cost per MT quantity of food grain at procurement center p
$coper_{b}$	Operational cost per MT quantity of food grain at base silo b
$Snum_{s}^{it}$	number of i types of trucks available at origin node s in time period t
$Pnum_{p}^{jt}$	number of j types of trucks available at procurement center p in time period t
$Bnum_{b}^{kt}$	number of k types of rakes available at base silo b in time period t
σ_{i}	capacity of i types of truck available at the origin node
e_{j}	capacity of j types of truck available at procurement centers
q_{k}	capacity of k types of rakes available at base silos
D_{f}^{t}	demand of field silo f during time period t
$dist_{sp}$	distance from origin node s to procurement center p
$dist_{sb}$	distance from origin node s to base silo b
$dist_{pb}$	distance from procurement center p to base silo b
$dist_{pb}$	distance from base silo b to field silo f by rail
G_{s}^{t}	Food grain quantity available at origin node s in period t
$Pcap_{p}$	Inventory holding capacity of procurement center p
$Bcap_{b}$	Inventory holding capacity of base silo b

4.2.3 Decision Variables

As per the present practices of the public distribution system in India, FCI has to decide that the, ''how much quantity, from which origin node, procurement centre, base silos, or field silos, when and where to transport". Therefore, in order to decide from which node-where to transport the food grains, allocation decisions (binary variables) needs to be taken into account from origin nodes to field silos. Initially, FCI takes the allocation decisions (binary variables) based on supply and demand of deficit states, then determines the amount of food grains to be transported (continuous variables) and a number of vehicles used (integer variables). The similar procedure of mathematical formulation with the combination of binary and continuous variables used by Mousavi et al. (2014).

Binary variables

X_{sp}^{t} $\begin{cases} 1 & \text{if origin node } s \text{ is allocated to procurement centre } p \text{ in period } t \\ 0 & \text{otherwise} \end{cases}$

Y_{pb}^{t} $\begin{cases} 1 & \text{if procurement center } p \text{ is allocated to base silo } b \text{ in period } t \\ 0 & \text{otherwise} \end{cases}$

V_{sb}^{t} $\begin{cases} 1 & \text{if origin node } s \text{ is allocated to base silo } b \text{ in period } t \\ 0 & \text{otherwise} \end{cases}$

Z_{bf}^{t} $\begin{cases} 1 & \text{if base silo } b \text{ is allocated to field silo } f \text{ in period } t \\ 0 & \text{otherwise} \end{cases}$

Continuous variables

m_{sp}^{t} Quantity of food grain transported from origin node *s* to procurement center *p* during time period *t*

h_{pb}^{t} Quantity of food grain transported from procurement center *p* to base silo *b* in time period *t*

g_{sb}^{t} Quantity of food grain transported directly from origin node *s* to base silo *b* in time period *t*

w_{bf}^{t} Quantity of food grain transported from base silo *b* to field silo *f* in time period *t*

α_{p}^{t} Quantity of food grain at procurement center *p* in time period *t*

β_{b}^{t} Quantity of food grain at base silo *b* in time period *t*

Integer Variables

n_{sp}^{it} number of *i* types of trucks used on arc *(s, p)* in time period *t*

v_{pb}^{jt} number of *j* types of trucks used on arc *(p, b)* in time period t

u_{sb}^{it} number of *i* types of trucks used on arc *(s, b)* during time period *t*

r_{bf}^{kt} number of *k* types of rakes used on arc *(b, f)* in time period t

4.3 Objective function

This study aims to determine the time-dependent movement and storage plan of food grain supply chain of three stages starting from farmers (origin nodes), procurement centers, base silos and field silos such that total cost of food grain supply chain is minimized. The overall objective function of the model is to minimize the total cost which comprises of transportation cost, operational cost and inventory holding cost. Various components of the objective function are described as follows. In the transportation cost, first and the second term gives shipment costs including fixed and variable costs from origin nodes to procurement centers and procurement centers to base silos, respectively. The direct transportation cost comprises of fixed and variable costs from origin nodes to base silos is represented by the third term. The last term provides the inter-state food grain movement cost containing fixed as well as variable costs from base silos to field silos. There are two terms in operational cost, in which first and second term indicates the operational cost at procurement centers and base silos, respectively. The inventory holding costs at procurement centers and base silos are included in inventory holding cost component of the objective function.

Minimize Total cost = Transportation Cost + Operational Cost + Inventory Holding Cost

Components of objectives

Transportation cost =

$$\sum_{s=1}^{S}\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{t=1}^{T}\left[\left(fc_{sp}^{i}.n_{sp}^{it}\right)+\left(dist_{sp}.vc_{\delta}.m_{sp}^{t}\right)\right].X_{sp}^{t}+\sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{j=1}^{J}\sum_{t=1}^{T}\left[\left(fc_{pb}^{j}.v_{pb}^{jt}\right)+\left(dist_{pb}.vc_{\delta}.h_{pb}^{t}\right)\right].Y_{pb}^{t}+$$
$$\sum_{s=1}^{S}\sum_{b=1}^{B}\sum_{i=1}^{I}\sum_{t=1}^{T}\left[\left(fc_{sb}^{i}.u_{sb}^{it}\right)+\left(dist_{sb}.vc_{\delta}.g_{sb}^{t}\right)\right].V_{sb}^{t}+\sum_{b=1}^{B}\sum_{f=1}^{F}\sum_{k=1}^{K}\sum_{t=1}^{T}\left[\left(fc_{bf}^{k}.r_{bf}^{kt}\right)+\left(dist_{bf}.vc_{\rho}.w_{bf}^{t}\right)\right].Z_{bf}^{t}$$

Operational Cost =

$$\sum_{t=1}^{T}\left[\sum_{s=1}^{S}\sum_{p=1}^{P}m_{sp}^{t}+\sum_{p=1}^{P}\sum_{b=1}^{B}h_{pb}^{t}\right].coper_{p}+\sum_{t=1}^{T}\left[\sum_{s=1}^{S}\sum_{b=1}^{B}g_{sb}^{t}+\sum_{p=1}^{P}\sum_{b=1}^{B}h_{pb}^{t}+\sum_{b=1}^{B}\sum_{f=1}^{F}w_{bf}^{t}\right].coper_{b}$$

Inventory holding cost =

$$\sum_{p=1}^{P}\sum_{t=1}^{T}\alpha_{p}^{t}.cinv_{p}+\sum_{b=1}^{B}\sum_{t=1}^{T}\beta_{b}^{t}.cinv_{b}$$

Subject to constraints

The various constraints of the model are described as below.

$$\sum_{p=1}^{P}\sum_{b=1}^{B}\left(m_{sp}^{t}.X_{sp}^{t}+g_{sb}^{t}.V_{sb}^{t}\right)\leq G_{s}^{t} \qquad \forall s,t \tag{1}$$

Constraint (1) restricts the food grain quantity transferred from an origin node to procurement centers and base silos, to maximum food grain quantity available at the origin node during each time period.

$$\sum_{b=1}^{B}\left(h_{pb}^{t}.Y_{pb}^{t}\right)\leq \alpha_{p}^{t} \qquad \forall p,t \tag{2}$$

$$\sum_{f=1}^{F}\left(w_{bf}^{t}.Z_{bf}^{t}\right)\leq \beta_{b}^{t} \qquad \forall b,t \tag{3}$$

Constraint (2) limits the food grain quantity transferred from procurement centers to the base silo, to maximum available inventory at given procurement center in given time period. Similarly, Constraint (3) shows the supply constraint of the base silo.

$$\alpha_{p}^{t=1}=0 \qquad \forall p,t \tag{4}$$

$$\beta_{b}^{t=1}=0 \qquad \forall b,t \tag{5}$$

The initial inventory at starting period in each procurement center and base silos is zero and represented by constraints (4) and (5), respectively.

$$\alpha_{p}^{t-1}+\sum_{s=1}^{S}\left(m_{sp}^{t}.X_{sp}^{t}\right)\leq Pcap_{p} \qquad \forall p,t \tag{6}$$

$$\beta_{b}^{t-1}+\sum_{s=1}^{S}\sum_{p=1}^{P}\left(g_{sb}^{t}.V_{sb}^{t}+h_{pb}^{t}.Y_{ob}^{t}\right)\ \leq\ Bcap_{b} \qquad \forall b,t \tag{7}$$

Constraints (6) and (7) ensures that inventory at procurement center and base silo does not exceed the inventory holding capacity of procurement center and base silo, respectively.

$$\sum_{b=1}^{B}\left(w_{bf}^{t}.Z_{bf}^{t}\right)=D_{f}^{t} \qquad \forall f,t \tag{8}$$

Constraint (8) depicts that total food grain quantity transferred from base silos must be equal to the demand of that particular field silo during time period t.

$$\alpha_{p}^{t-1}+\sum_{s=1}^{S}\left(m_{sp}^{t}.X_{sp}^{t}\right)-\sum_{b=1}^{B}\left(h_{pb}^{t}.Y_{pb}^{t}\right)=\alpha_{p}^{t} \qquad \forall p,t \tag{9}$$

$$\beta_{b}^{t-1}+\sum_{s=1}^{S}\sum_{p=1}^{P}\left(g_{sb}^{t}.V_{sb}^{t}+h_{pb}^{t}.Y_{pb}^{t}\right)-\sum_{f=1}^{F}\left(w_{bf}^{t}.Z_{bf}^{t}\right)=\beta_{b}^{t} \qquad \forall b,t \tag{10}$$

The inventory flow balance equations of procurement center and base silos are described by constraints (9) and (10), respectively.

$$\sum_{p=1}^{P} m_{sp}^{t}.X_{sp}^{t} \leq \sum_{p=1}^{P}\sum_{i=1}^{I}\left(n_{sp}^{it}.\sigma_{i}\right) \qquad \forall s,t \qquad (11)$$

$$\sum_{b=1}^{B} g_{sb}^{t}.V_{sb}^{t} \leq \sum_{b=1}^{B}\sum_{i=1}^{I}\left(u_{sb}^{it}.\sigma_{i}\right) \qquad \forall s,t \qquad (12)$$

$$\sum_{b=1}^{B} h_{pb}^{t}.Y_{pb}^{t} \leq \sum_{b=1}^{B}\sum_{j=1}^{J}\left(v_{pb}^{jt}.e_{j}\right) \qquad \forall p,t \qquad (13)$$

$$\sum_{f=1}^{F} w_{bf}^{t}.Z_{bf}^{t} \leq \sum_{f=1}^{F}\sum_{k=1}^{K}\left(r_{bf}^{kt}.q_{k}\right) \qquad \forall b,t \qquad (14)$$

Constraints (11) and (12) make sure that maximum food grain quantity transported from origin node to procurement center and origin node to base silo must be less than or equal to the maximum capacity of all trucks being used in that period on the same path, respectively. Similarly, Constraints (13) and (14) illustrates the truck and rake capacity constraints from procurement center to base silos and base silo to field silo, respectively.

$$\sum_{p=1}^{P}\sum_{b=1}^{B}\left(n_{sp}^{it}+u_{sb}^{it}\right) \leq Snum_{s}^{it} \qquad \forall s,i,t \qquad (15)$$

$$\sum_{b=1}^{B} v_{pb}^{jt} \leq Pnum_{p}^{jt} \qquad \forall p,j,t \qquad (16)$$

$$\sum_{f=1}^{F} r_{bf}^{kt} \leq Bnum_{b}^{kt} \qquad \forall b,k,t \qquad (17)$$

Constraint (15) guarantees that the number of trucks used on the route *(s, p)* and *(s, b)* must be less than or equal to the maximum trucks available at the origin node *s* in each time period. In the same way, Constraint (16) limits the number of trucks employed on the route *(p, b)*, to maximum trucks available at the procurement center during given time period. Furthermore, a number of rakes used on the route *(b, f)* must be less than or equal to the maximum rakes available at the base silos in each time period and same represented by the Constraint (17).

$$X_{sp}^{t}, Y_{pb}^{t}, V_{sb}^{t}, Z_{bf}^{t} = \{0,1\} \qquad \forall s,p,b,f,t \qquad (18)$$

$$m_{sp}^{t}, h_{pb}^{t}, g_{sb}^{t}, w_{bf}^{t}, \alpha_{p}^{t}, \beta_{b}^{t} \geq 0 \qquad \forall s,p,b,f,t \qquad (19)$$

$$n_{sp}^{it}, v_{pb}^{jt}, u_{sb}^{it}, r_{bf}^{kt} \in Z \qquad \forall s,p,b,f,i,j,k,t \qquad (20)$$

Constraints (18) – (20) portrays the binary, continuous and integer variables respectively used in the model.

5. Solution approach

In order to minimize the food grain supply chain cost, a MINLP model is formulated in the previous section after the critical analysis of Indian food grain supply chain scenario and taken into account the various factors such as fixed and variable cost of different capacitated vehicles along with their limited availability, capacitated procurement centers and base silos, operational and inventory cost in procurement centers and base silos, procurement quantity and demand of field silos. In FCTP problems, the presence of fixed costs makes the objective function discontinue and to get the solution of these FCTP problems in deterministic polynomial time is very difficult. (Antony Arokia Durai Raj & Rajendran, 2012; Balaji & Jawahar, 2010; Jawahar & Balaji, 2012). The current three-stage food grain transportation and storage problem also fall under the category of FCTP. Furthermore, due to the inclusion of several aforementioned factors into the problem, it becomes more complex and challenging problem.

Furthermore, to solve FCTP problems, typical MIP solution methods like a branch and bound method, cutting plane method are inefficient and computationally expensive. The linearization of the model requires the essential decomposition algorithm or process for linearizing the non-linear equations. The formulated mathematical model is non-linear in nature and complex due to the several decision variables including binary, integer and continuous along with a huge number of real life constraints. The number of variables and constraints increases exponentially as the problem size increases. In some cases, the product of binary and continuous decision variables can be linearized by incorporating new variable into the model, which has to take the value of the product. However, linearization process would increase the computational time inevitably due to the need of additional constraints satisfaction (Yu et al. 2017). Therefore, many authors have proposed the different metaheuristics like GA, SA, Tabu Search (TS) and Ant Colony Optimization (ACO) to solve the FCTP within reasonable computational time (Armentano, Shiguemoto, and Løkketangen, 2011; Panicker et al., 2013; Xie & Jia, 2012). Similarly, the chemical reaction inspired algorithm, called Chemical Reaction Optimization (CRO) was proposed by Lam and Li (2010) and many researchers have successfully implemented the CRO to solve the complex NP-hard problems (Lam, Li, & Yu, 2012; Truong, Li, & Xu, 2013). In recent times, the performance of CRO algorithm has been improved by hybridization with other algorithms like TS, SA and Differential Evolution (DE) algorithm (Li and Pan, 2013; Roy, Bhui and Paul, 2014). The CRO algorithm is inefficient at exploration (global search) and PSO often quickly stuck into the local minima. Therefore, the HP-CRO algorithm was recently developed by taking advantage of the compensatory property of CRO and PSO and proven to be effective for optimization problems (Li et al. 2015; Nguyen et al. 2014; Zhang and Duan 2014). Hence, we have employed this recent HP-CRO algorithm to solve the formulated MINLP model.

5.1 Chemical reaction optimization

CRO captures the chemical reaction phenomenon of molecules which tries to attain the stable state with low energy. A molecule is the key manipulating agent in CRO and candidate solution for a specific problem is stored or encoded into it. While searching the solution space, each molecule depicts the one point and provides the likely solution to the problem. In CRO, the change in molecular structure occurs when molecules collide with each other or wall of the container. A molecule has many characteristics such as structure (M_ω), Potential Energy (PE), Kinetic Energy (KE) and Number of hit (Numhit) etc. PE represents the objective function value of the corresponding solution. KE is a non-negative number and used for jumping out of local optima. The total number of moves (collisions) of the molecule is stored into the NumHit. The following four distinct elementary reactions with different energy manipulation approaches would take place because of collisions under different conditions. 1. *On-wall ineffective collision, 2. Decomposition, 3. Inter-molecular ineffective collision. 4. Synthesis.* The on-wall and inter-molecular ineffective reactions perform the intensification (local search), whereas decomposition and synthesis reaction handles the diversification (global search) in CRO. The description of these four reactions is given as follows.

1. On-wall ineffective operator

The on-wall ineffective collision takes place when a single molecule hits the wall of the container and bounces away as a singular entity. In this collision, a neighborhood search operator gives the new molecule ($M_{\omega'}$) by perturbing the original molecule (M_ω). Therefore the molecular structure and PE of a new molecule is slightly different from the original molecule. This collision will occur only if

$$PE_\omega + KE_\omega \geq PE_{\omega'} \tag{21}$$

Then we obtain,

$$KE_{\omega'} = \left(PE_\omega + KE_\omega - PE_{\omega'}\right).a \tag{22}$$

Where $a \in \left[KELossRate, 1\right]$ and (1- a) indicates the random number and fraction of KE lost to the surrounding environment, respectively. The remaining energy is transferred to the central energy buffer which activates the decomposition reaction.

$$buffer = buffer + \left(PE_\omega + KE_\omega - PE_{\omega'}\right).\left(1-a\right) \tag{23}$$

An original molecule with same structure remains in the population without any change, if Eq. (21) does not satisfied. The pseudocode of on-wall ineffective collision is given in Fig. 3.

Algorithm 1. On-wall ineffective collision

Input : Molecule M_ω

$\omega' \leftarrow N(\omega)$

$\mathrm{PE}_{\omega'} \leftarrow f(\omega')$

if $PE_\omega + KE_\omega \geq PE_{\omega'}$ **then**

Get $a \in \left[KELossRate, 1\right]$

Set $KE_{\omega'} = \left(PE_\omega + KE_\omega - PE_{\omega'}\right)a$

Update buffer = $buffer + \left(PE_\omega + KE_\omega - PE_{\omega'}\right)\left(1-a\right)$

Update M_ω, PE_ω and KE_ω

end if

Output : Molecule M_ω

Fig. 3. Pseudocode of on-wall ineffective collision

2. Inter-molecular ineffective collision

An Inter-molecular ineffective collision represents the situation when two randomly selected molecules M_{ω_1} and M_{ω_2} collide with each other to generate the two new molecules $M_{\omega_1'}$ and $M_{\omega_2'}$. This collision is also not a vigorous like on-wall ineffective collision due to the production of new molecules from their own neighbourhoods. This reaction will take place when following criteria meet.

$$PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2} \geq PE_{\omega_1'} + PE_{\omega_2'} \tag{24}$$

The energy released is given by:

$$E_{\text{inter}} = \left(PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2}\right) - \left(PE_{\omega_1'} + PE_{\omega_2'}\right) \tag{25}$$

We get

$$KE_{\omega_1'} = E_{\text{inter}}.p \tag{26}$$

$$KE_{\omega_2'} = E_{\text{inter}}.(1-p) \tag{27}$$

The remaining energy is disseminated in two newly generated molecules by means of uniformly generated random number *p* in the range of [0, 1]. The detailed steps of inter-molecular ineffective collision are shown in the form of pseudocode in Fig. 4.

Algorithm 2. Intermolecular ineffective collision

Input : Molecules M_{ω_1} and M_{ω_2}

$\omega_1' \leftarrow N(\omega_1)$ and $\omega_2' \leftarrow N(\omega_2)$

$\mathrm{PE}_{\omega_1'} \leftarrow f(\omega_1')$ and $\mathrm{PE}_{\omega_2'} \leftarrow f(\omega_2')$

$E_{\text{inter}} \leftarrow \left(PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2}\right) - \left(PE_{\omega_1'} + PE_{\omega_2'}\right)$

if $(E_{\text{inter}} \geq 0)$ **then**

Get $p \in [0,1]$

Set $KE_{\omega_1'} = E_{\text{inter}}\, p$

$KE_{\omega_2'} = E_{\text{inter}}\,(1-p)$

Update $M_{\omega_1}, PE_{\omega_1}, KE_{\omega_1}$ *and* $M_{\omega_2}, PE_{\omega_2}, KE_{\omega_2}$

end if

Output : Molecule M_{ω_1} and M_{ω_2}

Fig. 4. Pseudocode of intermolecular ineffective collision

3. Decomposition and Synthesis operator

In decomposition, a single molecule hit the wall of the container and decomposed into two new molecules with a very different structure from the original structure. This operator is used for exploration of new search space after local search carried out by the on-wall ineffective collision. To generate more number of molecules, additional energy that depends on two random numbers $\left(p_1, p_2 \in [0,1]\right)$ can be taken from the central energy buffer. The energy conservation equation of decomposition reaction is given as follows:

$$PE_{\omega} + KE_{\omega} + p_1.p_2.buffer \geq PE_{\omega_1'} + PE_{\omega_2'} \tag{28}$$

The following equation gives the energy involved.

$$E_{\text{deco}} = \left(PE_{\omega} + KE_{\omega} + p_1.p_2.buffer\right) - \left(PE_{\omega_1'} + PE_{\omega_2'}\right) \tag{29}$$

Next, the remaining energy is transformed into two newly generated molecules using the following equations where $p_3 \in [0,1]$.

$$KE_{\omega_1'} = E_{deco}.p_3 \tag{30}$$

$$KE_{\omega_2'} = E_{deco}.(1 - p_3) \tag{31}$$

$$buffer' = (1 - p_1 p_2)buffer \tag{32}$$

Synthesis operator performs the opposite action of decomposition and it take place when below criteria satisfy.

$$PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2} \geq PE_{\omega'} \tag{33}$$

The remaining energy is provided by:

$$KE_{\omega'} = PE_{\omega_1} + PE_{\omega_2} + KE_{\omega_1} + KE_{\omega_2} - PE_{\omega'} \tag{34}$$

In this paper, these two global search operators are not utilized due to their low efficiency (Lam, Li, & Yu, 2012).

5.2 Particle swarm optimization

The PSO is a stochastic optimization technique based on the movement and intelligence of swarms. It was inspired by social behavior of bird flocking or fish schooling. The PSO searches the global optima in the solution space through the set of particles flying over the solution space. Initially, the population of particles which correspond to the molecules in CRO is randomly initialized. Each particle depicts the possible solution of the problem and the swarm represents the population of solutions. The position and velocity are the two paramount features of each particle. Every particle tries to attain the better position in the solution space by learning from the cognitive knowledge of its experiences and social knowledge of the swarm. A particle reaches to the new position using the updated velocity and after the attainment of a new position, the best position of each particle and the best position of the swarm are updated as required. Next, the velocity of each particle is adjusted based on the experiences of the particle. These steps are repeated until a stopping criterion is satisfied. The velocity and position of the pioneer particle in traditional PSO is updated using the equations (35) and (36).

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot \delta \cdot (p_i(t) - x_i(t)) + c_2 \cdot \psi \cdot (p_g(t) - x_i(t)) \tag{35}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{36}$$

Where, $v_i(t)$ and $v_i(t+1)$ is the velocity of particle *i* in *t*th and *(t+1)*th iteration, respectively; $x_i(t)$ and $x_i(t+1)$ is the position of particle *i* in *t*th iteration and *(t+1)*th iteration; $p_i(t)$ is the local best position (pbest) of *i*th particle in *t*th iteration; $p_g(t)$ is the global best position (gbest) in *t*th iteration; *w* is the inertia weight; c_1 is the cognitive weight and c_2 is a social weight and δ, ψ are the two uniform random numbers in the range of [0, 1].

The expression (35) and (36) are used to make the cluster or swarm of the population of particles which are moving in a random direction. While updating the new elements sometimes, it takes the value out of boundaries. Therefore, in order to make sure that each updated particle lies within its predefined boundaries, its position is checked using boundary constraint handling methods at the end of the iteration. In this paper, we have employed the reflecting technique of boundary constraint handling which is shown in equation (37). During reflecting method, boundary acts as a mirror and reflects the projection of the particle's displacement which is flying outside of a parameters boundary.

$$x_i^{'} = \begin{cases} 2\times u_i - x_i & if\ x_i > u_i \\ 2\times l_i - x_i & if\ x_i < l_i \end{cases} \tag{37}$$

The PSO is easy for implementation to any problem and adaptable to control the balance between local and global exploration of the problem space. This approach of PSO helps to overcome the premature convergence of elite strategy in HP-CRO and improves the searching ability. The Fig. 5 shows the pseudocode of the *PSOUpdate* operator used in the HP-CRO algorithm.

Algorithm 3. *PSOUpdate*

Input : Particle ith
 Update velocity of particle ith using below equation
 $v_i = w\cdot v_i + c_1\cdot\delta\cdot(p_i - x_i) + c_2\cdot\psi\cdot(p_g - x_i)$
 Update position of particle ith using below equation
 $x_i = x_i + v_i$
 Constraint handling by below equation of reflecting method
  if $x_i > u_i$ **then**
   $x'_i = 2u_i - x_i$
  end if
  if $x_i < l_i$ then
   $x'_i = 2l_i - x_i$
  end if
Output : Particle ith with a new value

Fig. 5. Pseudocode of *PSOUpdate* operator

5.3 HP-CRO algorithm

5.3.1 Description of proposed approach

The HP-CRO algorithm is the combination of PSO and CRO algorithm. A solution can be changed through the *PSOUpdate* global search operator and CRO local search operator. PSO and CRO algorithms functioning on the identical initial size of the population. HP-CRO generates the new molecules using the neighbouring operators of CRO and PSO mechanisms. These newly generated molecules considered as molecules in the context of CRO or as particles in the perspective of PSO. Molecular structure (M_ω) represents the solution of the problem in specific format, i.e. number, vector or even a matrix. In this paper, a solution of the problem is stored into a vector which comprises of binary, continuous and integer variables. Each molecule (particle) corresponds to sets of binary variables (assignment variables), continuous variables (food grain quantity transported and stored in silos) and integer variables (number of vehicles used). A schematic representation of molecule (particle) for problem instance 1 (S=3, P=3, B=2, F=3, T=2) is presented in Fig. 6. Basic CRO has two global operators that are not used in the HP-CRO algorithm, hence the population size does not change and α, β parameters are excluded. Two local search operators, i.e. on-wall ineffective and inter-molecular ineffective operators are employed in HP-CRO. There is an update operator in PSO algorithm, called as a *PSOUpdate* operator. This *PSOUpdate* operator along with parameters set up and boundary constraints handling is implemented for exploration of search space of HP-CRO algorithm. The exploration (global search) and exploitation (local search) in the HP-CRO algorithm have well balanced using *PSOUpdate* operator and CRO local search operators, respectively. In the perspective of algorithmic parameters, this algorithm adopts all PSO parameters as well as few CRO parameters excluding α, β and append a new parameter (γ) for control of algorithm.

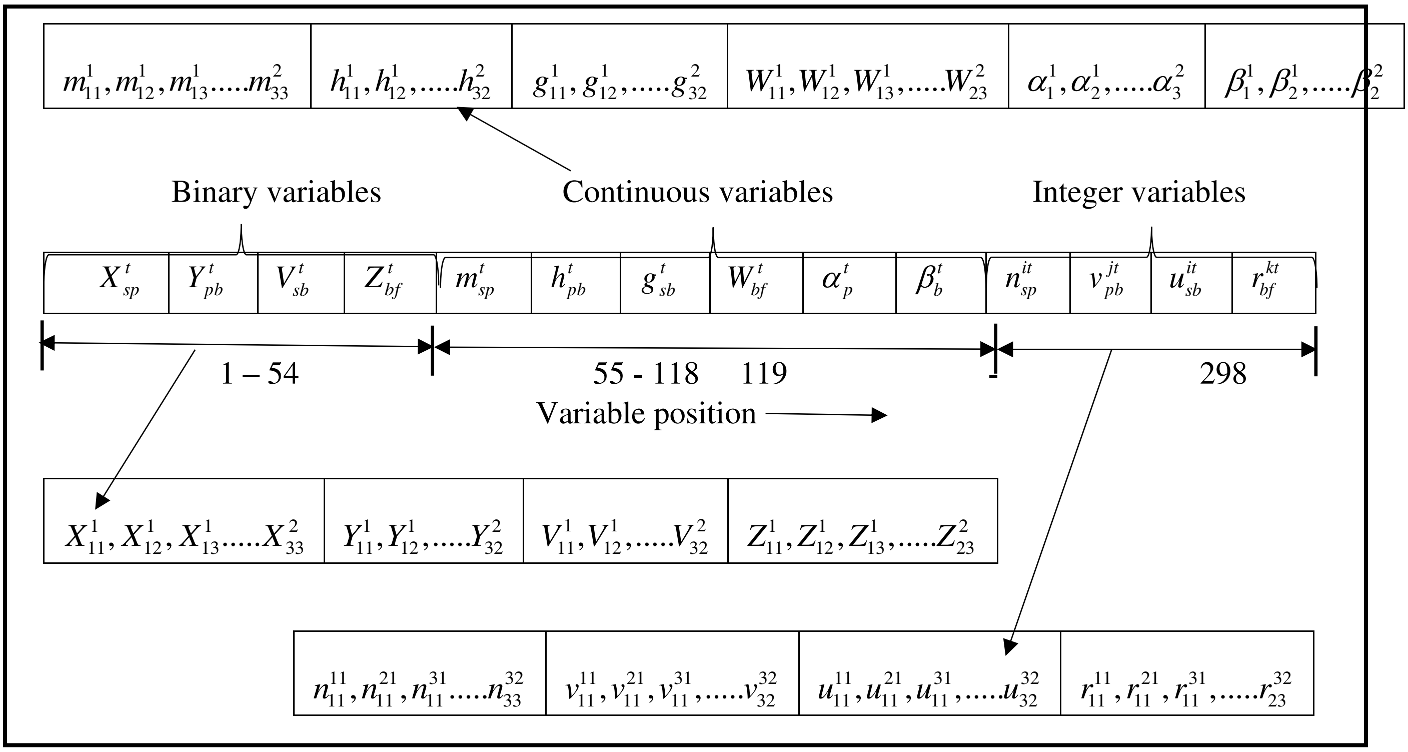

Fig. 6. The representation of a molecule (particle) of propose HP-CRO for problem instance 1

5.3.2 Main algorithm

Similar to the other metaheuristics, HP-CRO algorithm is sequentially implemented in three stages: Initialization, Iteration and Final stage (Termination). The detailed flowchart of the algorithm is given in Fig. 7. In each run, the algorithm starts with initialization, execute a number of iterations and stops at the final stage. Three stages are delineated in detail as follows:

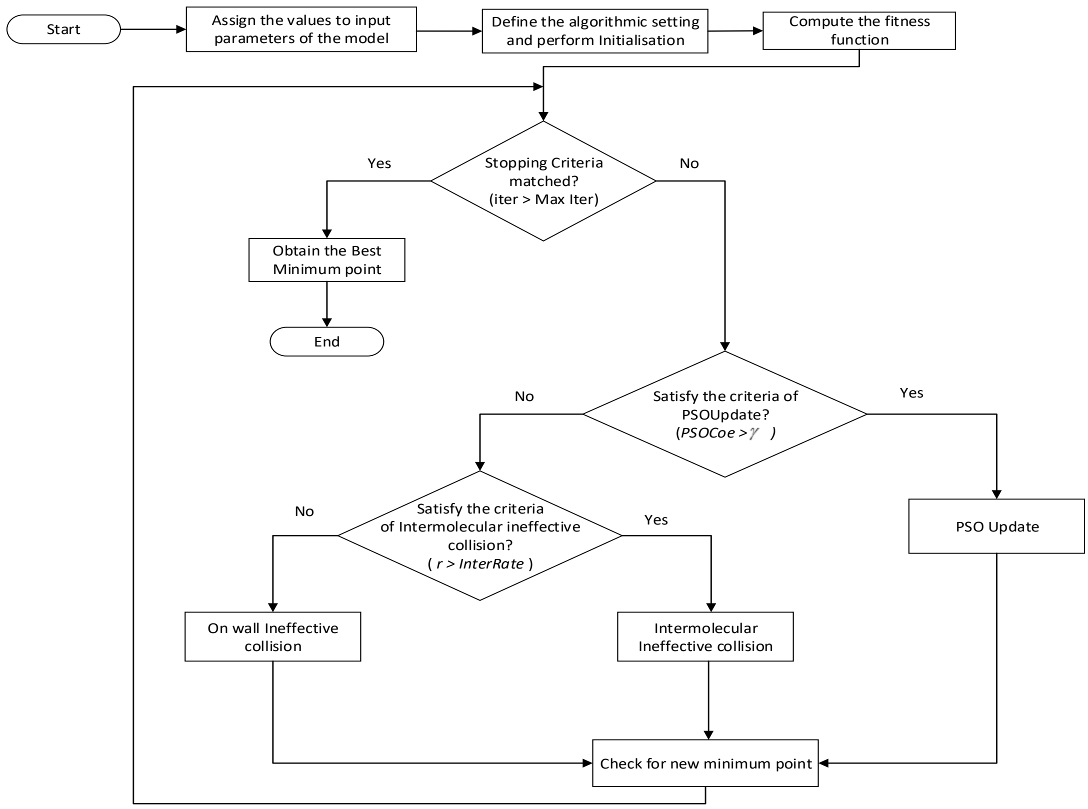

Fig. 7. Flowchart illustrating the working of HP-CRO algorithm

Stage 1:

Initially, the various inputs such as objective function, their constraints, and problem dimensions are given to the algorithm. In initialization stage, there is a need to assign the values to many variables and control parameters of an algorithm like *Pop_size, KELossRate, InitialKE, InterRate,* w, c_1, c_2, δ, and ψ, etc. The parameter *KELossRate* is utilized to restrict the maximum percentage of KE transmitted to buffer during each collision. InitialKE parameter represents the KEs original value of molecules in the population. Next, we randomly initialize the *Pop_size* number of solutions in the solutions space to produce the population and compute the fitness function of each molecule (particle). In the initialization phase, firstly the binary variables X^t_{sp}, Y^t_{pb}, V^t_{sb}, Z^t_{bf} pertaining to allocation of origin nodes, procurement centres, base silos and field silos are randomly selected. The random allocations lying in between [0, 1] are rounded to nearest binary integer numbers. Once nodes are assigned, quantities of food grains to be transferred among the four echelons is calculated. The quantity to be transported from origin node to procurement centre (m_{sp}^{t}) is determined considering the quantity available at origin node, the capacity of trucks available at origin node and procurement centres capacity in a given time period. Then, the number of different capacitated trucks used on arc *(s, p)* in given time period are estimated using quantities to be shipped (m_{sp}^{t}). Similar to the binary rounding, if a number of trucks used are found to be a continuous integer, then it is rounded to the nearest integer. Current inventory at procurement centre is updated and set equal to current inventory plus quantities arrived minus quantities shipped. Similarly, for other stages, quantity to be transported, vehicles used and updated values of inventory are decided in exactly same way as done in the case of origin node and procurement centre. Once the values of all the decision variables are known, the total cost for each molecule (particle) is found using the objective function. Constraints of the model are handled using the penalty function method. When a solution violates a specific constraint, then a penalty is added to the objective function value. This procedure makes sure that the infeasible solutions do not get selected because of poor objective function value. Furthermore, the penalty is included in the objective function value in proportion to the constraint violation. Therefore, the solution with less constraint violation is better than the one with more constraint violation.

Stage 2: During the iteration stage, the specific number of iterations are carried out after the random selection of molecule (particle) M_w from the population until the stopping criteria is satisfied. Then, in order to decide the type of search to be executed (left: on-wall ineffective collision or inter-molecular collision; right: *PSOUpdate*), the comparison criteria between PSO coefficient (*PSOCoe*) and γ is investigated. The balance between global and local search is maintained using the parameter γ. If the comparison criteria ($PSOCoe > \gamma$) is satisfied, then algorithm triggers the *PSOUpdate* operator (Algorithm 3). This means that the molecule M_w must be changed through global search operator after it undergoes γ times of local search. Otherwise, a unimolecular or intermolecular collision has to be selected based on the intermolecular collision Rate (*InterRate*) criteria. The moves of unstable molecules in container activates the collisions. A molecule can either hit on a wall of the container or collide with each other. The *InterRate* criteria shows that if randomly generated number *r*, in the range of [0, 1] is greater than the *InterRate,* then inter-molecular collision (inter-molecular ineffective collision) will take place. Otherwise, molecule follows the unimolecular collision (On-wall ineffective collision). Next, any new minimum point found in solution space is examined and stored. This iteration stage will continue until any one of the stopping criteria is met.

Stage 3: The algorithm will stop after satisfying the stopping criteria and provides the minimum total cost (best solution value) found in the final stage. The pseudocode of HP-CRO algorithm is given in Fig. 8.

Algorithm 4 HP-CRO

Input: Problem specific information (Objective function, constraints and the problem dimensions)
\\ Initialization
Set the algorithmic parameters values to $PopSize$, $KELossRate$, $Stepsize$, $buffer$, $InitialKE$, γ, $InterRate$, $w(inertia\ weight)$, $c_1(cognitive/local\ weight)$, $c_2(social/global\ weight)$.
Generate the PopSize number of molecules (Particles)
for each of molecules (particles) **do**
    Assign random solution to the molecular structure (particle position) ω
    Compute the fitenss function of ω by $f(\omega)$
    Set $PSOCoe = 0$
end for
\\ Iterations
while (the stopping criteria not satisfy) **do**
    Randomly select one molecule (particle) M_w from population
    if $(PSOCoe > \gamma)$ **then**
        Trigger $PSOUpdate\ (M_w)$
        $PSOCoe_{M_w} = 0$
    else
        Generate r randomly in the interval [0, 1]
        if $(r > InterRate)$ **then**
            Randomly select the molecules M_{w_1} and M_{w_2}
            Trigger the intermolecular ineffective collision (M_{w_1}, M_{w_2})
            $PSOCoe_{M_{w_1}} = PSOCoe_{M_{w_1}} + 1$
            $PSOCoe_{M_{w_2}} = PSOCoe_{M_{w_2}} + 1$
        else
            Trigger On-wall Ineffective Collision (M_w)
            $PSOCoe_{M_w} = PSOCoe_{M_w} + 1$
        end if
    end if
    Check for any new minimum solution
end while
\\ The final stage
Output: Best solution and its objective function value

Fig. 8. Pseudocode of HP-CRO

6. Computational results and discussion

This section describes the various developed problem instances, parameters setting of the proposed algorithm and computational experiments along with results and managerial insights.

6.1 Problem instances

In this paper, we develop the nine problem instances based on the secondary data gathered from many reliable sources. The paramount reliable sources include the CAG report 2013, High-level Committee report 2015, FCI portal (http://fci.gov.in) and PDS Portal of India (http://pdsportal.nic.in/main.aspx), etc. The summary of overall essential model parameter values required for solving the model is provided in Table 2. Each problem instance is characterized by the number of origin nodes (S), number of procurement centers (P), number of base silos (B), number of field silos (F) and number of time periods (T). The detail delineation of all the nine problem instances along with a total number of constraints and each type of total decision variables are mentioned in Table 3. Furthermore, all the problem instances are classified in three groups based on the total number of decision variables of the problem instances. The small size group of problem comprises of maximum 3000 variables and medium size includes up to 10000 variables. Finally, the problem instances with more than 10000 variables come under the group of large size. According to this sorting, all the nine problem instances are equally divided into three groups, i.e. small, medium and large size.

Table 2 Data ranges of parameters used in the model

Parameters	Range of values
Fixed cost of three different types of trucks used on arc *(s, p)*	200, 150, 100
Fixed cost of three different types of trucks used on arc *(s, b)*	200, 150, 100
Fixed cost of three different types of trucks used on arc *(p, b)*	300, 400, 500
Fixed cost of three different types of rakes at used on arc *(b, f)*	1000, 700, 500
Variable cost of road transportation	20
Variable cost of rail transportation	15
Inventory holding cost at procurement centres	150
Inventory holding cost at base silo	100
Operational cost at procurement centre	80
Operational cost at base silo	50
Number of i_1 types of trucks available at origin node	500-1000
Number of i_2 types of trucks available at origin node	600-1100
Number of i_3 types of trucks available at origin node	700-1200
Number of j_1 types of trucks available at procurement centre	600-1000
Number of j_2 types of trucks available at procurement centre	700-1100
Number of j_3 types of trucks available at procurement centre	800-1200
Number of k_1 types of rakes available at base silo	6-15
Number of k_2 types of rakes available at base silo	8-18
Number of k_3 types of rakes available at base silo	9-20
Capacity of i types of trucks (i = 1, 2, 3)	20, 18, 15
Capacity of j types of trucks (j = 1, 2, 3)	30, 25, 20
Capacity of k types of rakes (k = 1, 2, 3)	3000, 1800, 1500
Demand of field silo	15000-30000
Distance from origin node to procurement centre	10-50
Distance from origin node to base silo	20 - 70
Distance from procurement centre to base silo	40-100
Distance from base silo to field silo	500-1000
Food grain quantity available at origin node	20000-40000
Inventory holding capacity of procurement centre	30000-70000
Inventory holding capacity of base silo	50000-200000

Table 3 Dimensions of problem instances

Problem Instance size	Problem instance (S-P-B-F-T)	Origin node	Procurement centre	Base silo	Field silo	Time period	Constraints	Binary variables	Continues variables	Integer variables
Small size	Instance 1 (3-3-2-3-2)	3	3	2	3	2	1628	54	64	180
	Instance 2 (5-4-3-4-2)	5	4	3	4	2	7051	118	132	402
	Instance 3 (8-6-5-6-2)	8	6	5	6	2	41903	296	318	996
Medium Size	Instance 4 (12-9-7-8-2)	12	9	7	8	2	175602	622	654	2136
	Instance 5 (15-10-8-10-2)	15	10	8	10	2	348246	860	896	3000
	Instance 6 (18-12-10-12-2)	18	12	10	12	2	751978	1272	1316	4392
Large Size	Instance 7 (20-15-12-13-3)	20	15	12	13	3	2036328	2628	2709	8964
	Instance 8 (22-18-15-17-3)	24	20	15	18	3	4393254	3753	3852	12393
	Instance 9 (25-22-18-20-3)	28	25	20	23	3	8645029	5268	5388	17190

6.2 Parameter setting

The solution quality and convergence rate of evolutionary algorithms are mainly influenced by the parameter tuning of the algorithm (Wisittipanich & Hengmeechai 2017). Therefore, suitable parameters of the algorithms are essential to avoid the bad simulation results. The scientific methods of parameter tuning of metaheuristic are rare in the literature and it mostly depends on the experience of researchers. Furthermore, the comprehensive analysis of all possible combinations of parameters is impractical (Lam, Li and Yu 2012). Hence, the appropriate parameter values which give the good performance have been assigned through the numerous runs and analyses of problem instance 1 using the proposed algorithm. The crucial parameters of the HP-CRO algorithm are *Pop_Size, KELossRate, IntitalKE,* γ *, InterRate,* w (inertia weight), c_1 (cognitive/local weight), and c_2 (social/global weight). The performance of the proposed algorithms on problem instance 1 are investigated on ten different parameter combinations considering the various values of each parameter. The results of parameter tuning experiments are shown in Table 4 and the best values of parameters for each algorithm are highlighted in bold.

Table 4 The total cost of problem instance 1 according to the ten parameter tuning combinations

		Parameter tuning combinations									
Algorithm	Parameter	1	2	3	4	5	6	7	8	9	10
HP-CRO	Pop_size	50	100	150	200	150	**150**	200	150	100	50
	Iterations	100	200	300	400	100	**100**	300	100	200	300
	InitialKE	1000	850	10000	10000000	1000	**10000000**	10000	10000000	850	10000
	KELossRate	0.2	0.4	0.6	0.8	0.4	**0.2**	0.6	0.2	0.4	0.8
	γ	10	20	100	10	100	**10**	10	20	100	10
	InterRate	0.2	0.5	0.7	0.9	0.7	**0.2**	0.7	0.2	0.5	0.2
	Inertia weight	0.8	0.85	0.9	0.95	0.85	**0.9**	0.8	0.95	0.85	0.9
	Local weight	0.1	0.2	0.3	0.4	0.2	**0.1**	0.3	0.4	0.2	0.1
	Global weight	0.65	0.75	0.85	0.95	0.75	**0.95**	0.65	0.85	0.65	0.95
	Total cost (in millions of INR)	1938.9	1944.2	1935.3	1940.8	1937.1	**1932.0**	1940.3	1933.6	1945.9	1937.3
CRO	Pop_size	50	100	150	200	150	150	200	**150**	100	50
	Iterations	100	200	300	400	100	100	300	**100**	200	300
	InitialKE	1000	850	10000	10000000	1000	850	10000	**10000000**	850	10000
	KELossRate	0.2	0.4	0.6	0.8	0.4	0.6	0.6	**0.2**	0.4	0.8
	InterRate	0.2	0.5	0.7	0.9	0.7	0.9	0.7	**0.2**	0.5	0.2
	Alpha	15	50	200	15	50	200	15	**15**	15	50
	Beta	10	20	100	10	10	100	10	**10**	100	10
	Total cost (in millions of INR)	1975.5	1977.6	1972.6	1976.5	1985.9	1984.8	1979.5	**1970.8**	1982.3	1984
PSO	Pop_size	50	100	150	200	**150**	150	200	150	100	50
	Iterations	100	200	300	400	**100**	100	300	100	200	300
	Inertia weight	0.8	0.85	0.9	0.95	**0.9**	0.85	0.8	0.95	0.85	0.9
	Local weight	0.1	0.2	0.3	0.4	**0.1**	0.2	0.3	0.4	0.2	0.1
	Global weight	0.65	0.75	0.85	0.95	**0.95**	0.75	0.65	0.85	0.65	0.95
	Total cost ((in millions of INR)	2030.18	2040.43	2032.71	2043.6	**2025.34**	2036.56	2040.2	2028.45	2038.16	2030.87

6.3 Experimental results

In this subsection, the HP-CRO, CRO and PSO algorithms are coded in MATLAB R2014a and the codes are implemented on a machine with the configuration of Intel Core i5, 2.90 GHz processor with 8 GB RAM. In order to evaluate the performance of the proposed HP-CRO algorithm, initially, we solved all the generated problem instances using the HP-CRO algorithm. Similarly, all nine instances are solved using the original CRO and PSO algorithm under the same setting of population size and a number of iterations. Then, comparisons have been carried out between the numerical results obtained through HP-CRO, CRO and PSO algorithm. The computational results of 20 runs of each algorithm for each instance are reported in Table 5. This table illustrates the minimum, maximum, average and standard deviation of the total cost (in millions of INR) obtained from the each algorithm with computational time. Furthermore, the convergence behavior of the HP-CRO algorithm is compared with conventional CRO and PSO using the graph of total cost versus number of iterations as shown in Figs. 9(a), (b) and (c). According to the results from Table 5, the HP-CRO algorithm obtained better results in terms of minimum total cost (best solution) and maximum total cost (worst solution) of each instance compared with CRO and PSO. In addition, the average and standard deviation of the total cost of 20 runs of this algorithm are smaller than the CRO and PSO. The computational time taken by the HP-CRO to solve the each instance is less than CRO and PSO computational time. This overall result of nine problem instances enlightens the superiority of HP-CRO algorithm when compared with CRO and PSO algorithm. The convergence behavior of the algorithm is another crucial aspect for evaluation of its performance. Figs. 9(a), (b) and (c) clearly depict the faster convergence behavior of an HP-CRO algorithm compared to the basic CRO and PSO when solving each type of problem sizes. This shows that the HP-CRO needs the fewer number of iterations to search the best near optimal solution.

Table 5 The total cost comparison between HP-CRO and CRO

Instance	PSO (All cost in millions of INR)					CRO (All cost in millions of INR)					HP-CRO (All cost in millions of INR)				
	Minimum Cost	Maximum Cost	Avg Cost	SD of Cost	Time (s)	Minimum Cost	Maximum Cost	Avg Cost	SD of Cost	Time (s)	Minimum Cost	Maximum Cost	Avg Cost	SD of Cost	Time (s)
(3-3-2-3-2)	2010.23	2120.08	2072.15	35.21	21.63	1959.80	2046.50	2001.85	33.09	18.86	1922.00	1993.60	1953.94	24.79	14.90
(5-4-3-4-2)	2760.41	2980.63	2855.26	73.82	57.26	2697.60	2862.30	2762.85	50.51	46.64	2584.20	2730.30	2653.94	47.20	32.63
(8-6-5-6-2)	3560.75	3990.00	3845.54	131.42	110.30	3500.50	3824.60	3718.53	92.95	98.70	3372.40	3700.90	3537.66	85.19	80.57
(12-9-7-8-2)	5920.36	6050.18	5985.80	49.05	256.08	5889.30	5958.10	5925.94	26.17	211.78	5835.40	5904.90	5876.01	18.56	170.65
(15-10-8-10-2)	6650.00	6870.57	6756.27	84.88	348.72	6574.30	6781.90	6682.35	82.39	309.14	6455.60	6697.50	6600.23	82.07	237.80
(18-12-10-12-2)	8170.72	8400.14	8274.57	78.34	430.84	8129.90	8306.60	8204.09	63.28	405.50	8056.50	8218.20	8131.48	59.28	349.32
(20-15-12-13-3)	35900.61	39200.20	37780.50	816.22	689.16	35522.00	38355.00	37444.20	752.08	629.56	35342.00	37709.00	37147.09	688.48	515.05
(22-18-15-17-3)	57200.35	60800.08	59450.15	1054.36	942.73	56317.00	59968.00	58323.11	1026.35	885.92	54723.00	57549.00	56654.78	832.71	768.94
(25-22-18-20-3)	84700.60	90500.45	87300.79	1995.55	1023.47	83886.00	89821.00	86223.11	1835.33	956.60	83038.00	88594.00	85110.33	1695.35	817.62

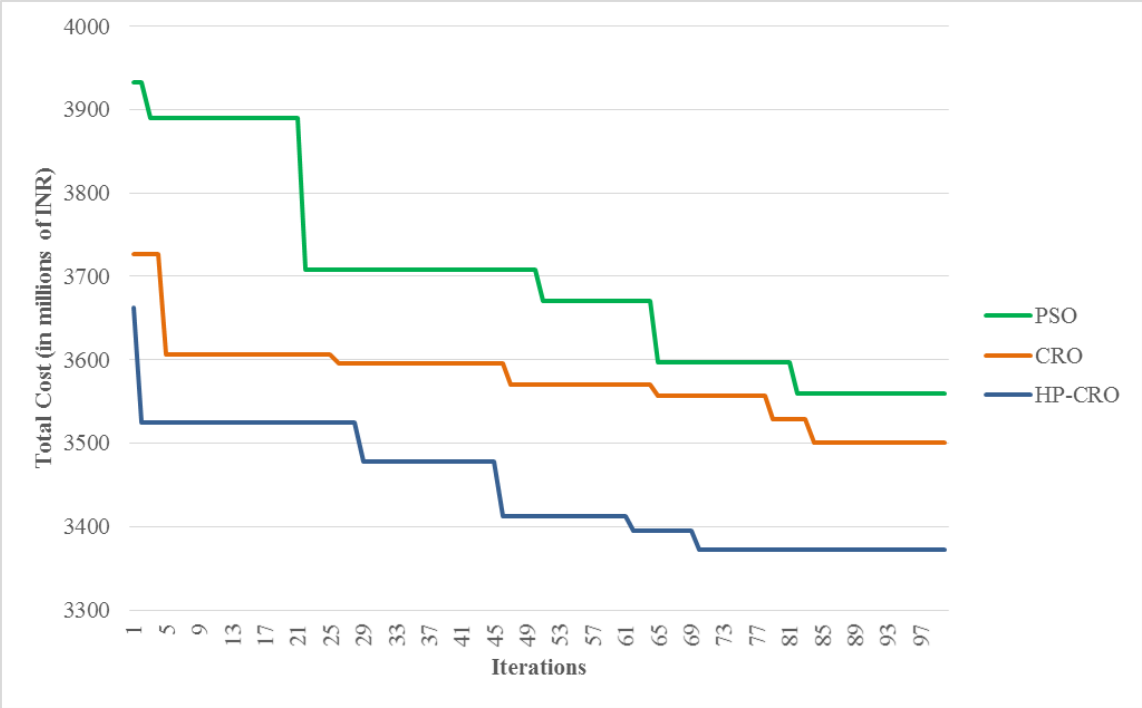

Fig. 9(a). Graph depicts the convergence behaviour of instance 3

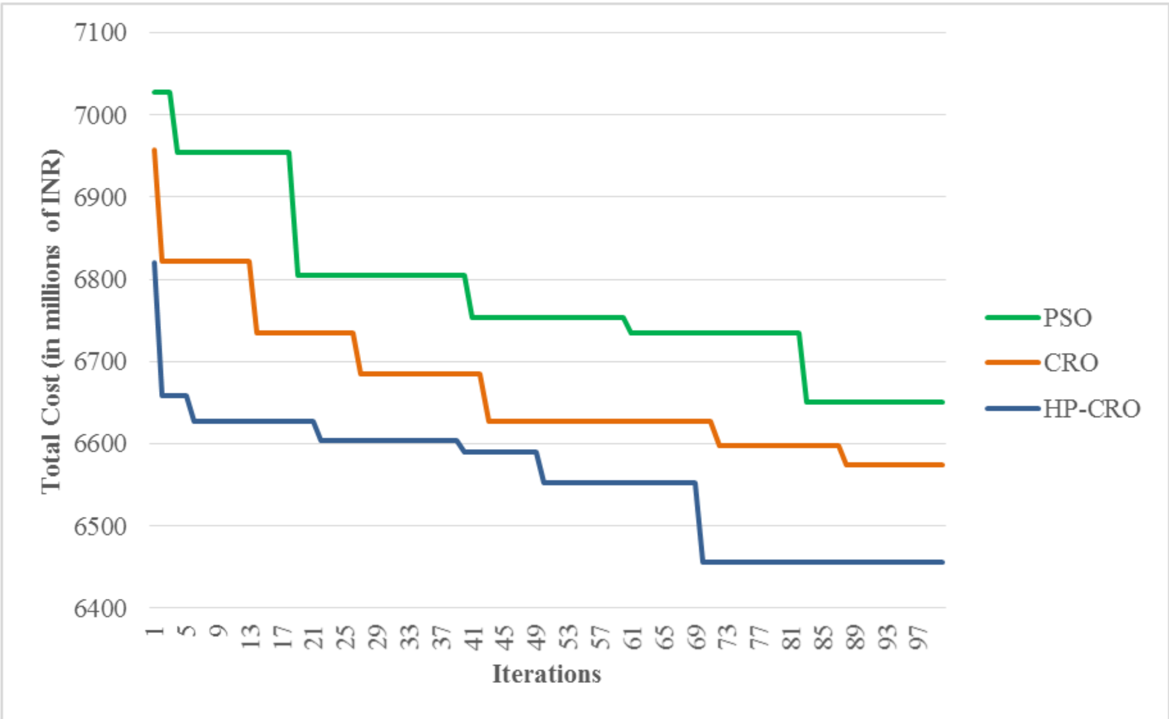

Fig. 9(b). Graph depicts the convergence behaviour of instance 5

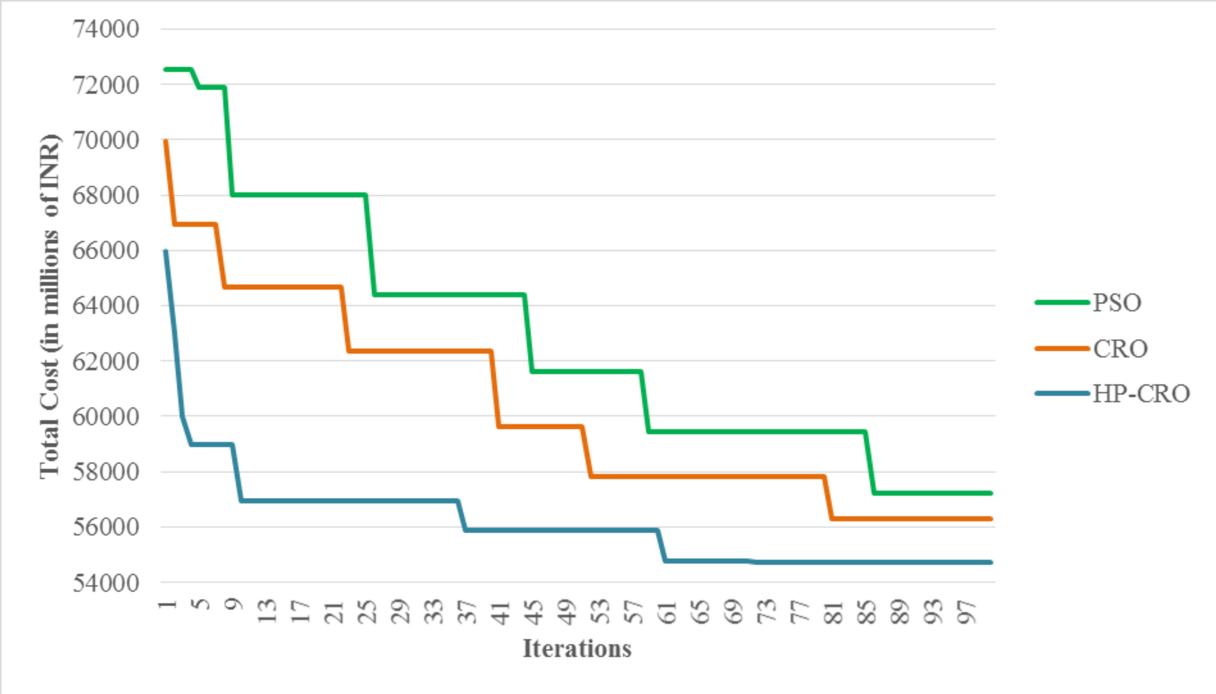

Fig. 9(c). Graph depicts the convergence behaviour of instance 8

The overall scenario of movement and storage activities of all the stages in a finite planning horizon for selected three instances is depicted in Figs. 10(a), (b) and (c). Therein, Fig. 10(a) provides the aggregate total quantity transported from each stage and inventory in procurement centers and silos. The total number of each type of trucks used during the particular time period of chosen three problem instances are depicted in Fig. 10(b). Similarly, Fig. 10(c) portrays the number of each type of rakes used between base silos and field silos in a given time period. Additionally, the comprehensive flow analysis of the problem instance 1 is shown in Fig. 11. The movement and storage activities of the second time period have not been shown in Fig. 11 for the clarity. The quantity transferred and each type of vehicles used between the particular nodes are represented on the upper side and lower side of the arc, respectively. The food grain quantity shipped from origin nodes to base silos is more than those transferred to procurement centers because of the less waiting time, low handling cost and fully mechanized facility at the base silo. The results of this model will be very helpful for making the timely movement and storage activity plan of FCI. The issue of shortages of trucks as well as rakes can be effectively tackled through proper planning and coordination between the FCI, railways and private contractors. The FCI and SGAs can prepare the plan of a number of each type of vehicles required for transportation in advance using the available procured quantity and inventory in each time period. Moreover, the vehicle scheduling and optimal utilization of resources are another important decisions which governed by the movement and storage plan of FCI. The huge amount of food grain supply chain cost and losses can be reduced by the effective and efficient movement as well as storage of food grain in bulk form rather than a conventional method of gunny bags.

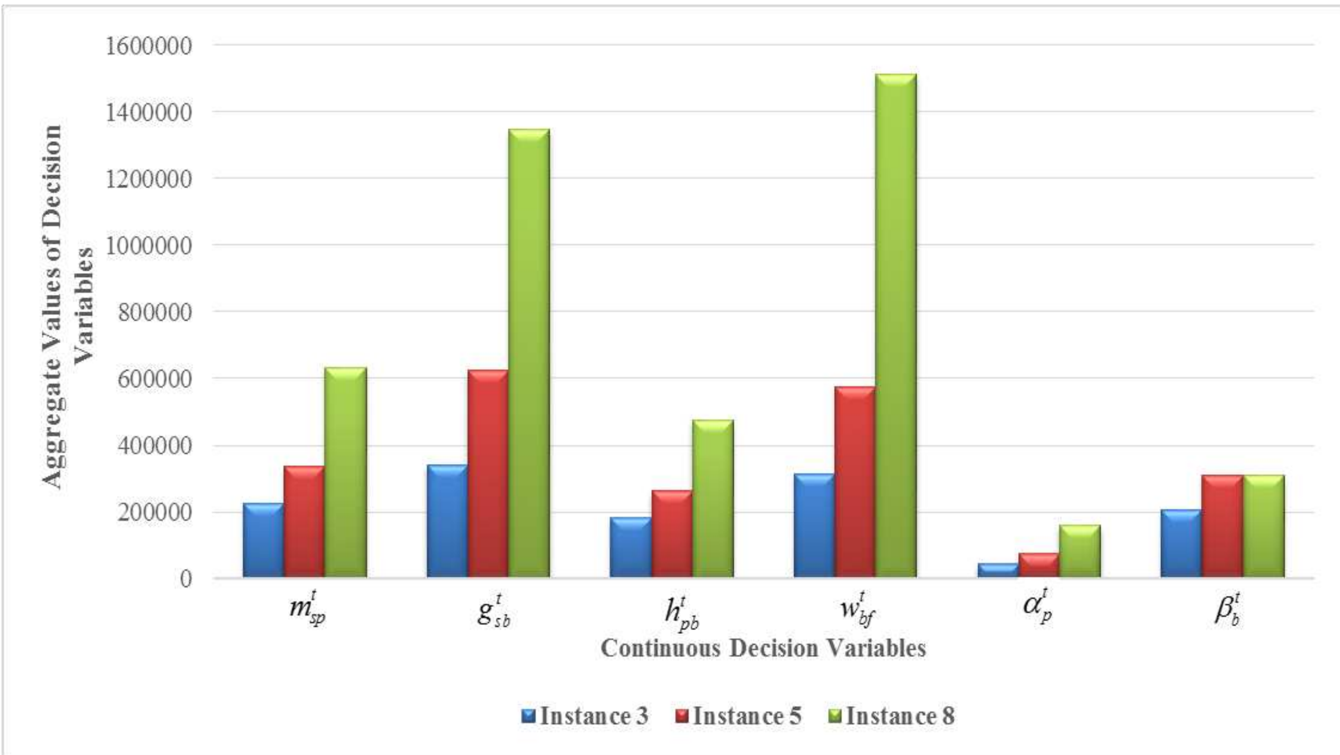

Fig. 10(a). The sample aggregate values of continuous variables (food grain quantity transported and stored) of three different instances

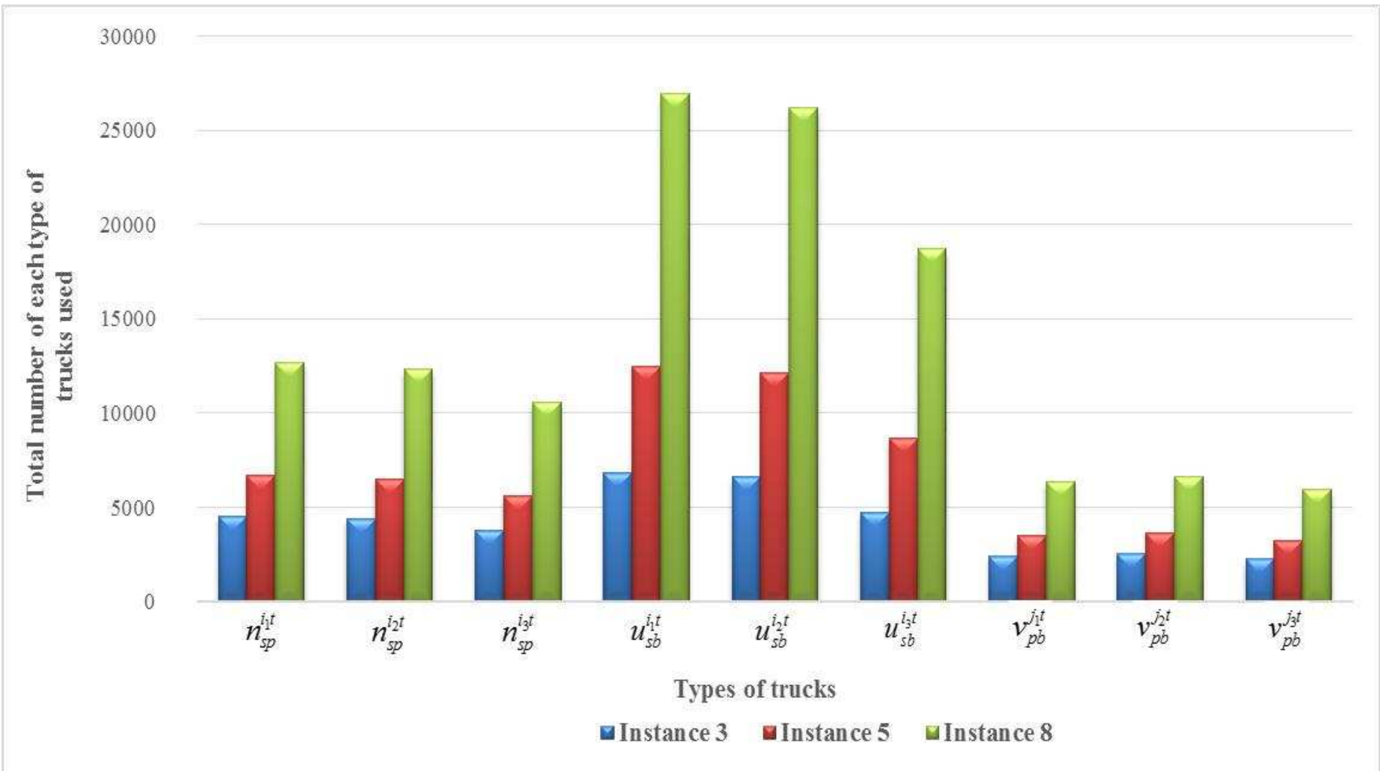

Fig. 10(b). The total number of each type of vehicles (trucks) used in three different instances

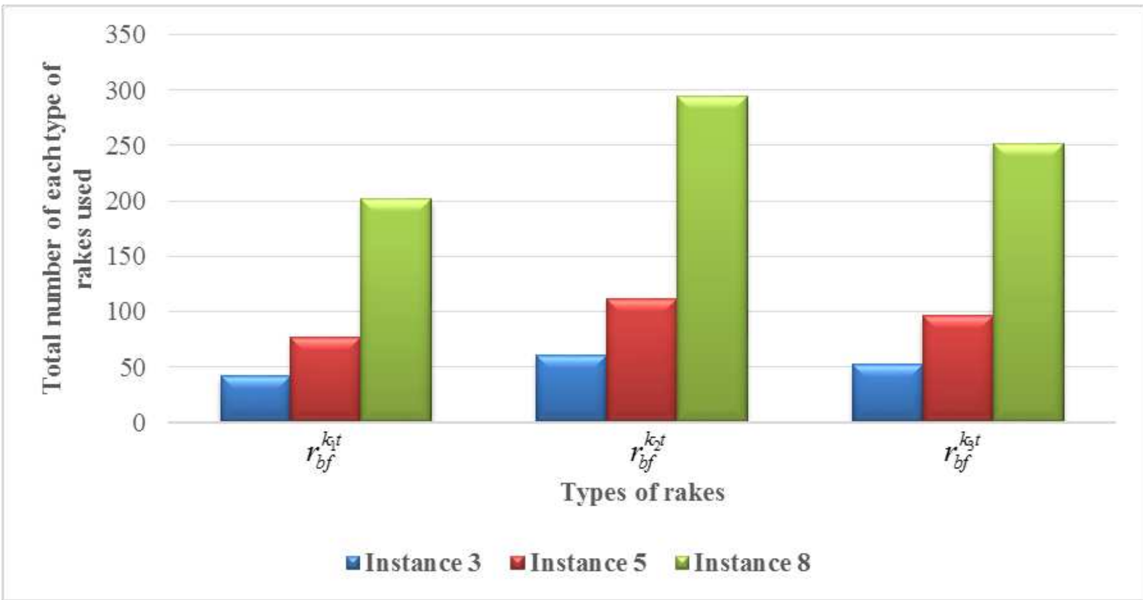

Fig. 10(c). The total number of each types of vehicles (rakes) used in three different instances

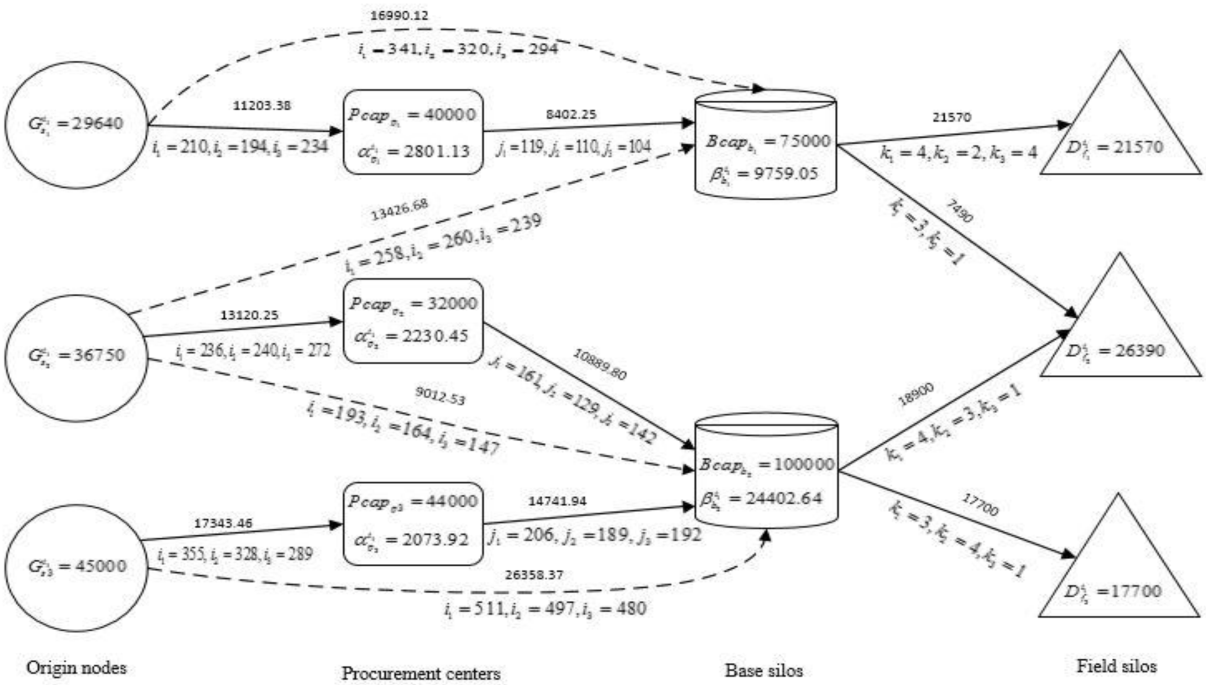

Fig. 11. Detailed analysis of food grain supply chain network of problem instance 1

7. Conclusions and future work

This paper examines the new problem of three stage food grain distribution in India, including the origin nodes, procurement centers, base silos and field silos where farmers can sell their food grain directly to FCI at base silos or SGAs in the procurement centers. The mathematical model in the form of MINLP is formulated to minimize the transportation, inventory and operational cost of food grain. The various realistic aspects are taken into account while formulating the model such as the fixed and variable cost of transportation, capacitated silos, inventory and operational cost of food grain, seasonal procurement, deterministic demand and finite planning horizon. Due to the non-linear nature, numerous binary and integer variables along with a huge number of constraints, mathematical model has been solved using the recently established HP-CRO and results attained are validated using the original CRO and PSO. The results of the computational experiments of all the generated problem instances clearly illustrate that the HP-CRO algorithm finds the good quality solutions with faster convergence rate compared to basic CRO and PSO. The valuable insights evolved from this research can be useful to take the proper planning and coordination decisions among the many entities involved in the food grain supply chain like FCI, SGAs, Railways and private contractors. This study can be extended by relaxing the some of the assumptions in the model like deterministic demand and procurement. The multi food grain distribution is another topic for future work. Furthermore, the performance of the algorithm can be enhanced through the comprehensive analysis of the parameter values.

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